The Bioeconomics of Climate Change Adaptation: Coffee Berry Borer and Shade-Grown Coffee.

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Abstract

Research on climate change in recent decades has disproportionately focused on predicting impacts while largely ignoring adaptation strategies. How agricultural systems can adapt to minimize the uncertainty caused by rising temperatures is one of the most important research issues today. We focus on the coffee berry borer, the most important coffee pest worldwide, which has recently expanded across the tropics as a result of rising temperatures, threatening coffee farms worldwide. Intercropping shade trees with coffee trees is being promoted as a promising climate change adaptation strategy that can protect coffee plantations from micro-climate variability and reduce pest infestations. Little is known, however, on whether or not the benefits of the ecological services provided by shade trees justify the ensuing yield reduction associated with shade-grown coffee production systems. We develop a computational, bioeconomic model to analyze the ecological and economic sustainability of switching from a sun-grown to shade-grown coffee system as a climate change adaptation strategy. In particular, we model the spatial-dynamic pest diffusion at the plant level and evaluate alternative shading strategies based on farm expected net present values. Using parameters from Colombia, preliminary model findings suggest that the ecological benefits of shade-grown planting systems justify the forgone revenues from lower per acre yields only for high levels of shading. We solve for the threshold net price premium of shade-grown coffee that would make this climate change adaptation strategy cost-effective at moderate shading levels.

Key words: Bioeconomic Models, Cellular Automata, Colombia, Computational Methods, Ecological Services, Pest Control, Coffee Berry Borer. *JEL Codes*: C63, Q54, Q57.

Research on climate change in recent decades has disproportionately focused on predicting impacts of climate change as opposed to examining promising adaptation strategies. Consequently, very little is known about the benefits and costs of adaptations to climate change in specific agricultural and agroforestry systems (Antle and Capalbo 2010). For example, production of coffee, the most valuable tropical export crop worldwide, has been recently affected by increasing temperatures and consequent damages due to a variety of pests and diseases (Jaramillo et al. 2011). In particular, the coffee berry borer (CBB), which is the most damaging coffee pest in all coffee-producing countries, has recently expanded its presence into higher elevations as a result of rising temperatures across the tropics (Mangina et al. 2010). CBB damage is likely to worsen over time because of a projected increase in both the number of insect generations per year and the number of eggs laid per female borer (Jaramillo et al. 2010). The damage may increase poverty and food insecurity among approximately 120 million people in South America, East Africa, and Southeast Asia (Vega et al. 2003; Jaramillo et al. 2011). CBB is likely to be especially severe in Latin America where the pest lacks natural enemies (Avelino, ten Hoopen and DeClerck 2011). Small-scale, asset-poor coffee producers would be disproportionately affected because of their limited financial ability to invest in costly adaptation strategies as well as in more intensive pest and disease management strategies.

Production technologies can be adapted to minimize the uncertainty in coffee production under rising temperatures in tropical areas. Intercropping shade trees with coffee trees has been promoted as a rational, economically feasible, and relatively easy-to-implement climate change adaptation strategy (Lin 2006; Blackman et al. 2008; Jaramillo 2011; Jaramillo et al. 2013). Shade trees can decrease the temperature around coffee berries by 4 to 5°C (Beer et al. 1998; Jaramillo 2005). Such temperature reduction would imply a drop of 34 percent in the CBB's

intrinsic rate of increase (Jaramillo et al. 2009). Jaramillo et al. (2013) found that CBB infestation levels in shaded plantations never reached the economic threshold whereas this threshold was almost always reached in sun-grown plantations. Moreover, coffee berry borer densities tend to be lower in shaded coffee plantations because of the increased biodiversity and the ensuing higher populations of natural enemies (Perfecto et al. 2005; Teodoro et al. 2009). Such pest control ecosystem services have been valued at US $75-310 ha-year $^{-1}$ in Costa Rica in terms of avoided damages (Karp et al. 2013). In addition, integrated pest management, which includes insect trapping, is more successful in shaded than in unshaded coffee plantations (Dufour et al. 2005). Shade-grown coffee farmers may receive a price premium for their coffee or direct payments for the by-products and ecosystem services they provide (Somarriba 1992; Ferraro, Ushida, and Conrad 2005; Kitti et al. 2009; Barham and Weber 2012). Finally, they may have an additional income through the sale of timber. In the American tropics, laurel (*Cordia alliodora* (Ruiz and Pavón) Oken) is a fast-growing, valuable timber species that regenerates naturally and abundantly in coffee fields and is a source of income for coffee farmers (Mussak and Laarman 1989; Somarriba 1992; Somarriba et al. 2001). Disentangling the ecological services and opportunity costs of switching from sun-grown to shade-grown coffee systems requires careful bioeconomic, spatial-dynamic modeling.

The literature on shade-grown coffee has focused on ecological and agronomic trade-offs implied by the intercropping of coffee plants with shade plants (Haggar et al. 2011; Jaramillo et al. 2013). However, we are not aware of research examining the economics of shade-grown coffee as a climate change adaptation strategy to reduce pest infestations. In particular, it is not clear whether the expected net economic benefits of switching from sun-grown to shade-grown coffee systems offset the costs. To fill this gap in the literature, in this paper we develop a

bioeconomic model that uses bioeconomic parameters from the CBB literature to simulate pest diffusion and alternative shading strategies to examine whether and under which conditions the economic and ecological benefits provided by shade trees justify the ensuing yield reduction associated with shade-grown production systems.

Literature Review

The unique characteristics of certain pests restrict the choice of modeling approaches of pest diffusion and control. The first characteristic is that pest infestations are simultaneously driven by spatial-dynamic biophysical processes. Pest diffusion is affected by the farm's spatial configuration, the density and location of individual host and non-host plants (Avelino, ten Hoopen and DeClerck 2011). In the case of shade coffee, for example, modeling the probability of infestation for an individual coffee plant would need to be specified, in each time step, as a function of whether neighboring plants are shade or coffee trees and whether neighboring coffee trees are infested and at what level. Second, the low-mobility and host-specificity characteristic of CBB (Avelino, ten Hoopen and DeClerck 2011), and the local effect of a coffee tree's microclimate on the reproduction of the CBB (Jaramillo et al. 2009) make it most appropriate to choose the plant as the modeling unit in a spatial diffusion model. Third, if the goal is to experiment with alternate coffee farm configurations, where coffee plants are intercropped with shade plants, a grid-based model is most suitable. Taken together, these three characteristics call for grid-based, plant-level, spatial-dynamic models of pest diffusion and control.

Spatial Bioeconomic Models

Spatial-dynamic processes have only recently been studied by economists and the bioeconomic literature on agricultural diseases, pests, and invasive species control is mostly

nonspatial thus possibly leading to the recommendation of suboptimal managerial decisions (Sanchirico and Wilen 1999, 2005; review in Wilen 2007). In most existing spatial models, and consistently with the application in question, spatial heterogeneity is modeled as exogenous and fixed over time (e.g., barriers to disease diffusion or constant, location-dependent state-transition probabilities). In the case of some pests including CBB, however, spatial heterogeneity is neither exogenous, nor fixed over time. A healthy plant's probability of being infested is conditional on the health status of its neighborhood which, in turn, is endogenously determined by the spatial-dynamic pest diffusion process and the implementation of management strategies. The challenge of incorporating such spatial feedbacks into state dynamics is a common thread in resource economics and not confined to pest and disease dynamic models (Smith, Sanchirico and Wilen 2009). Addressing this challenge usually precludes analytical solutions and calls for numerical methods in most applications.

Cellular Automata

Cellular automata and individual-based models have become the preferred methodological framework to study socio-ecological complex systems such as diseases and pests in agro-ecosystems (Grimm and Railsback 2005; Miller and Page 2007). Cellular automata are dynamic models that operate in discrete space and time on a uniform and regular lattice of cells. Each cell is in one of a finite number of states that get updated according to mathematical functions and algorithms that constitute state transition rules. At each time step, a cell computes its new state given its own old state and the old state of neighboring cells according to transition rules specified by the modeler (Tesfatsion 2006; Wolfram 1986). The spatial-dynamic structure is especially relevant when modeling processes that face physical constraints (Gilbert and Terna, 2000) as in the case of pest and disease diffusion in agricultural and agroforestry systems.

Although cellular automata models have been extensively employed to model spatial-dynamic ecological processes including pest diffusion (e.g. BenDor et al. 2006; Prasad et al. 2010), their use in the agricultural and resource economics literature has been rare (Atallah et al. 2014).

The present work attempts to assess, from a joint economic and ecological standpoint, the introduction of shade trees in a coffee farm as a response to climate change-driven increased CBB infestations. We contribute to the bioeconomic and climate adaptation literature by developing a plant-level model where the effect of climate adaptation measures on pest diffusion is modeled at the plant level, in a spatial-dynamic way. We formally define the bioeconomic model, then build the computational model and parameterize it using CBB ecology and coffee agroforestry literature field data. Using simulation experiments, we generate distributions of bioeconomic outcomes for the scenario of no infestation, the strategy of no climate change adaptation (sun-grown system) and five alternative climate change adaptation strategies, namely five shade-grown systems. We then conduct statistical analyses to rank the expected net present values generated in each experiment to identify the optimal strategy. Finally, we conduct sensitivity analyses to key bioeconomic model parameters. We synthesize our modeling process in Table 1.

[Insert table 1 here]

Bioeconomic Model

The spatial geometry of pest diffusion is represented by a two-dimensional grid G representing a coffee farm. G is the set of I x J cells where I and J are the number of rows and columns, respectively. In our model, there are 1,681 cells $(i, j) \in G$, each being occupied by either a coffee plant or a shade plant (laurel). Farm rows are oriented north to south with I=41 cells per grid row

and *J*=41 cells per grid column a representing a one-hectare coffee plantation with 1,681 coffee trees.[1]

Each cell (i, j) has a tree type state $\boldsymbol{\tau}_{i,j}$, an infestation state $\boldsymbol{s}_{i,j,t}$, and an age state $\boldsymbol{a}_{i,j,t}$. State $\boldsymbol{\tau}_{i,j}$ is a *2 × 1* vector holding a *1* if a cell holds a coffee tree and a zero if the cell holds a shade tree. State $\boldsymbol{s}_{i,j,t}$ is the infestation state vector of a coffee plant. The vector, of dimension *4×1*, holds a *1* for the state that describes a plant's infection state and zeros for the remaining three states. A coffee tree can be either *Healthy* or *Infested* at a *low*, *moderate*, or *high* level. The three levels of infestation refer to the percentage of berries in each tree that are infested with CBB (figure 4, Jaramillo et al. 2013). Given that CBB infestation is host-specific, a shade tree can only be in the *Healthy* state (Avelino, ten Hoopen and DeClerck 2011). State $\boldsymbol{a}_{i,j,t}$is a *9,125×1* vector holding a *1* for a tree's age in days and a zero for the other ages.

Time t progresses in discrete daily steps up to 9,125 days or approximately 25 years. A coffee plant's revenue is known to the farmer at time t. Yet, the per-plant revenue is random for periods beyond t as it depends on the coffee plant's infestation state $\boldsymbol{s}_{i,j,t}$. The revenue from a cell is a random variable $r\left(\boldsymbol{\tau}_{i,j}, \boldsymbol{s}_{i,j,t}, \boldsymbol{a}_{i,j,t}\right)$ that depends on the type of tree occupying the cell ($\tau_{i,j}$), its infestation state ($\boldsymbol{s}_{i,j,t}$), and its age ($\boldsymbol{a}_{i,j,t}$). For a cell occupied by a coffee plant, revenue is equal to $r_{coffee}(\boldsymbol{s}_{i,j,t})$ and is function of the infestation state only (equation 0a). Yield reduction ($\widetilde{y_{s_{i,j,t}}}$) is equal to 2%, 6%, and 20% when CBB berry infestation is *low* (10%), *moderate* (40%), and *high* (90%), respectively. A quality penalty ($\widetilde{p_{s_{i,j,t}}}$) is also imposed on coffee berries with CBB defects. This penalty is equal to 3%, 23%, and 43% for the three infestation levels (I_L, I_M and I_H), respectively. The revenue from a cell occupied by a shade plant is equal to $r_{shade}(\boldsymbol{a}_{i,j,t})$ and is function of the age state only (0b). It is equal to zero until the shade tree reaches the age of full productivity at which point the cell revenue is equal to the

product of the timber yield (y_{shade}) and price (p_{shade}).[2] Symbols, definitions, values, and references for the parameters are presented in table 2.

(0a) $$r_{coffee}(\boldsymbol{s}_{i,j,t}) = y_{(s_{i,j,t}=Healthy)} * \left(1 - \widetilde{y_{s_{i,j,t}}}\right) * p_{(s_{i,j,t}=Healthy)} * (1 - \widetilde{p_{s_{i,j,t}}})$$

(0b) $$r_{shade}(\boldsymbol{a}_{i,j,t}) = \begin{cases} 0 & if\ a_{i,j,t} < \tau_{max} \\ y_{shade} * p_{shade}\ if\ a_{i,j,t} \geq \tau_{max} \end{cases}$$

[Insert table 2 here]

Given each coffee plant's state $\boldsymbol{s}_{i,j,t}$, and an infestation state transition matrix $\boldsymbol{P}$, its expected infestation state $\mathrm{E}(\boldsymbol{s}_{i,j,t+1})$ at time $t+1$ is computed according to the following infestation-state transition equation:

(1) $$\mathrm{E}(\boldsymbol{s}_{i,j,t+1}) = \boldsymbol{P}^{\mathrm{T}}\, \boldsymbol{s}_{i,j,t}$$

where E is the expectation operator and $\boldsymbol{P}^{\mathrm{T}}$ is the transpose of matrix $\boldsymbol{P}$. The left-hand side of equation (1) $\mathrm{E}(\boldsymbol{s}_{i,j,t+1})$ is a *4* x *1* vector with a probability of staying in the current infestation state, a probability of transitioning to the next state, and zeroes elsewhere.

We now describe how the infestation state transition probability matrix $\boldsymbol{P}$ governs the plant-level CBB diffusion. Coffee plants in state *Healthy (H)* are susceptible to CBB infestation. CBB attacks a *Healthy* coffee plant with a neighborhood-dependent conditional probability *b*. Infestation starts at the *low* level. The transition from state *Infested-low* to state *Infested-moderate* happens with a conditional probability d. Similarly, transition from state *Infested-moderate* to state *Infested-high* happens with a conditional probability f. Mathematically, $\boldsymbol{P}$ can be expressed as follows:[3]

(3) $$\boldsymbol{P} = \begin{pmatrix} 1-b & b & 0 & 0 \\ 0 & (1-d) & d & 0 \\ 0 & 0 & (1-f) & f \\ 0 & 0 & 0 & 1 \end{pmatrix}$$

In equation (3), b is the *Healthy* to *Infested-low* transition probability conditional on previous own, and neighborhood infestation states and current own, and neighborhood tree type states. It can be expressed as

(4) $$b = \Pr\left(s_{i,j,t+1} = I_{low} \,\middle|\, s_{i,j,t} = H\right)$$

$$= \begin{cases} 0 \text{ if } N_{i,j,t} = (no\ shade\ plant, no\ infested\ coffee\ plants) \\ 1 - e^{-\alpha} \text{ if } N_{i,j,t} = (no\ shade\ plant, at\ least\ one\ infested\ coffee\ plant) \\ 0 \text{ if } N_{i,j,t} = (at\ least\ one\ mature\ shade\ plant, no\ infested\ coffee\ plants) \\ 1 - e^{-\beta} \text{ if } N_{i,j,t} = (at\ least\ one\ mature\ shade\ plant, at\ least\ one\ infested\ coffee\ plant) \end{cases}$$

In equation (4), $N_{i,j,t}$ is a state that indicates whether there are any infested coffee plants and mature shade trees among the eight neighbors of a coffee plant (figure 1). This type of neighborhood, called Moore neighborhood, is consistent with observed patterns of CBB diffusion where the pest is shown to spread from tree to tree without any directional preference (Ruiz-Cárdenas et al. 2009). Consider a healthy coffee plant that is surrounded by healthy coffee plants with or without shade plants. The probability that it will get infested in the next time step is equal to zero. If it has at least one infested neighbor, a plant-to-pant infestation occurs with rate parameter α if the coffee tree's neighborhood does not contain any mature shade tree. That is, the time a coffee tree with at least one *Infested* neighbor stays in the *Healthy* state before transitioning to the *Infested-low* state, is an exponentially distributed random variable, with rate α. If a healthy coffee plant has at least one infested neighbor and at least one mature shade plant in its neighborhood, a plant-to-plant infestation occurs with rate parameter β. Given that shade reduces CBB's intrinsic rate of increase (Jaramillo et al. 2009), parameter β is smaller than parameter α. In each time step (i.e., on any day during the production season), a random variable u_t determines whether the *Healthy* to *Infested-low* state transition happens or not. A *Healthy* coffee tree that has one *Infested* neighbor and no mature shade tree around it is infested

by the pest at time *t+1* if $u_t < 1 - e^{-\alpha}$, where u_t is a random draw from $U \sim (0, 1)$. Conversely, the pest does not colonize the neighboring tree if $u_t \geq 1 - e^{-\alpha}$. When two or more infestation types are realized (e.g., when a coffee tree has one *Infested* neighbor to the north and one *Infested* neighbor to the southwest), the state transition is determined by the infestation type that is realized first (Cox 1959).

[Insert figure 1 here]

The probability of transitioning from *Infested-low (I_L) to Infested-medium (I_M)* is given by conditional probability d as follows:

$$(5) \qquad d = \Pr\left(s_{i,j,t+1} = I_M \,\middle|\, s_{i,j,t} = I_L\right) = \begin{cases} 1 - e^{-1/L_1} & \text{if } N_{c,i,j,t} \text{ has no shade plant} \\ 0 & \text{otherwise} \end{cases}$$

This probability also depends on a coffee plant's neighborhood state. Coffee trees that have a mature shade plant in their neighborhood never reach the *Infested-medium* state (figure 4, Jaramillo et al. 2013). Those that do not have a mature shade plant in their neighborhood spend a period L_1 in state *Infested-low* (I_L) before they transition to state *Infested-moderate* (I_M). The waiting time after a coffee tree enters state I_L and before it transitions to state I_M is a random variable, exponentially distributed with fixed rate parameter $1/L_1$.

The *Infested-medium (I_M)* to *Infested-high (I_H)* state transition probability is given by conditional probability f as follows:

$$(6) \qquad f = \Pr\left(s_{i,j,t+1} = I_H \,\middle|\, s_{i,j,t} = I_M\right) = \begin{cases} 1 - e^{-1/L_2} & \text{if } N_{c,i,j,t} \text{ has no shade plant} \\ 0 & \text{otherwise} \end{cases}$$

This probability also depends on a coffee plant's neighborhood state. Coffee trees that have a mature shade plant in their neighborhood never reach the heavily infested state (figure 4, Jaramillo et al. 2013). For coffee trees that do not have a mature shade tree in their neighborhood, the waiting time after they enter state *Infested-moderate* (I_M) and before they

transition to state *Infested-high* (I_H) is a random variable, exponentially distributed with fixed rate parameter $1/L_2$. Symbols, definitions, values, and references for the model parameters are presented in table 3.

[Insert table 3 here]

The objective of a risk-neutral coffee farmer is to maximize the farm's ENPV by choosing an optimal shading strategy from a set of strategies, $\mathcal{W}$. Each strategy consists of a share of shade trees in the coffee farm and translates into a binary decision for each cell (i, j) at the beginning of each simulation whereby $u_{i,j,0} = 1$ if a coffee plant is removed and replaced with a shade plant and 0 otherwise for each (i, j) at $t = 0$. Once a coffee plant has been replaced, it takes the shade tree τ_{max} periods to reach maturity at which point it has an economic value and provides shade to its neighboring coffee trees thus reducing conditional probabilities b, d and f.

The optimal strategy $\mathcal{W}^*$ is therefore the set of cell-level control variables $\{u_{i,j,0}\}$ that allocates effort over space so as to yield the maximum ENPV over time. Letting E be the expectation operator over the random cell-level revenues $r\left(\boldsymbol{\tau}_{i,j}, \boldsymbol{s}_{i,j,t}, \boldsymbol{a}_{i,j,t}\right)$ and ρ^t the discount factor [4] at time *t* (in days) where $t \in \{0, 1, 2, \ldots, 9125\}$, the objective of a coffee farmer is to maximize the expected net present value (ENPV) as follows:

$$(7)\quad \max_{\mathcal{W}} \mathrm{E} \sum_t^T \rho^t \sum_{(i,j)}^G \left\{ \begin{array}{c} \left(1 - \sum_{\tau=0}^{\tau_{max}} u_{i,j,0}\right)\left[r\left(\boldsymbol{\tau}_{i,j,t}, \boldsymbol{s}_{i,j,t}, \boldsymbol{a}_{i,j,t}\right) - c_{i,j,t}(N_{i,j,t})\right] \\ -u_{i,j,0}\left(c_{u_{i,j,0}} + c_{u_{i,j,t}}\right) \end{array} \right\}$$

subject to:

$$(1)\qquad \mathrm{E}(\boldsymbol{s}_{i,j,t+1}) = \boldsymbol{P}^{\mathrm{T}}\, \boldsymbol{s}_{i,j,t}$$

The first expression in the square brackets of equation (7) represents the revenue of a plant in location(i, j), which depends on its tree type ($\boldsymbol{\tau}_{i,j,t}$), infestation ($\boldsymbol{s}_{i,j,t}$) and age ($\boldsymbol{a}_{i,j,t}$) states at time *t*. If the farmer has decided to remove a coffee plant in cell (i, j) and replace it with a shade

plant at $t = 0$, then $u_{i,j,0}$ is equal to 1 and the revenue from that cell is equal to zero for τ_{max} periods thus capturing the opportunity cost of having temporarily unproductive shade trees in the coffee farm. The shade tree revenue is equal to $r_s(\boldsymbol{a}_{i,j,t})$ thereafter, capturing the opportunity cost of having lower economic value in cells occupied by shade trees as opposed to coffee trees. If the farmer has left the coffee plant in cell (i, j) $t = 0$, then $u_{i,j,0}$ is equal to 0 and the revenue from that cell is equal to $r_c(\boldsymbol{s}_{i,j,t})$ minus the unit cost of coffee production $c_{i,j,t}$. Note that the unit cost of coffee production depends on the state of its neighborhood $N_{i,j,t}$: it is lower if there is at least one mature shade tree in the neighborhood of the coffee tree. This allows the model to be consistent with experimental findings that per-tree cost of coffee production is lower in shade-grown systems compared to sun-grown systems, mostly due to fewer fertilizer requirements (Chamorro, Gallo, and López 1994, table 3).[5] Binary variable $u_{i,j,0}$ pre-multiplies two unit costs associated with shade trees. The first unit cost, $c_{u_{i,j,0}}$, is the cost of removing the coffee plant and planting the shade tree. This cost occurs only at t=0. If a farmer has left cell (i, j) occupied with a coffee plant at $t = 0$, then $u_{i,j,0}$ is equal to 0, i.e., the farmer does not incur any costs associated with growing shade trees. The second unit cost, $c_{u_{i,j,t}}$, is the unit production cost of shade trees.

Model Initialization

The beginning of the simulation represents the beginning of a calendar year. Coffee trees are initialized as *Healthy*. In September, when berries are ripe, a small percentage (0.5 percent) of the coffee plants are chosen at random from a uniform spatial distribution U $(0, I * J)$ to transition from *Healthy* to *Infested-low*. This reflects findings in CBB studies indicating that infested coffee berries from the previous growing season act as a source of re-infestation in the following season (Jaramillo et. al 2006). In addition, fourteen[6] coffee plants situated in the northwestern border of the farm are chosen at random to transition from *Healthy* to *Infested-low*.

This reflects findings in Ruiz-Cárdenas et al. (2009) that CBB might be introduced from neighboring coffee farms. Subsequently, CBB spreads to *Healthy* coffee trees according to the state transition described in equation (1) until harvest, which occurs in December. At harvest, CBB populations drop. We model season-to-season re-infestation by letting all *Infested-moderate* and *Infested-high* trees transition back to *Infested-low* after harvest but never to state *Healthy.* Infested coffee trees stay in state *Infested-low* until the berries of the next growing season have reached maturity in the following September and pest diffusion resumes.

Model calibration and parameterization

Currently the model uses parameters from the CBB ecology literature and has not been calibrated (table 3). We plan to use spatio-temporal data in Ruiz-Cárdenas et al. (2009) and temporal data in Jaramillo et al. (2013) to calibrate the model. In order to select the CBB infestation rates in no shade and shade conditions (parameters α and β in table 3), we will first define a calibration objective function that minimizes the difference between the total number of infested coffee trees over time obtained from our computational model under no shade production, and the total number of infested coffee trees over time and space from Ruiz-Cárdenas et al. (2009) and Jaramillo et al. (2013). Next, we will use an optimization engine (OptQuest ^{TM}) that varies the values of α and β in each of the Monte Carlo simulations according to an algorithm combining Tabu search, scatter search, integer programming and neural networks, to find the optimal parameter values (Step 2c. in table 1). We choose a daily time step to be consistent with the time units of CBB diffusion parameters (Railsback and Johnson 2011).

Experimental Design

We design and implement Monte Carlo experiments to evaluate a discrete set of shading strategies by comparing their bioeconomic outcomes to those resulting from a strategy of no shade. Each experiment consists of a set of 300 simulation runs, over 9,125 days (25 years), on a coffee farm of 1,681 coffee trees. Experiments differ in the fraction of shade trees to total number of trees in the coffee farm. We experiment with shading strategies that have a fraction of shade trees below and above the 5-6% fraction (70 shade trees/acre approximately) required for shade-grown coffee certifications (SAN 2010). We consider the following shading strategies: 0 (sun-grown), 2, 4, 6, 8, and 10% shading levels.

Survey data indicate that, in most cases, timber shade trees are recruited from the naturally occurring regeneration (Somarriba 1992 and references therein); we therefore assign the location of shade trees using random draws from a uniform distribution.

Outcome realizations for a run within an experiment differ due to random spatial initialization of the infestation and the shading strategies and due to subsequent random spatial pest diffusion. Data collected over simulation runs are the expected values of the bioeconomic outcomes under each strategy (Step 3, table 1): expected net present values and average CBB prevalence. In order to find the optimal shading strategy, we employ the objective function (equation 7) to rank the coffee farm net values under the alternative strategies. Finally, we conduct statistical tests to rank the shading strategies and find the optimal strategy (Step 4, table 1). The model is written in Java and simulated using the software AnyLogic^{TM} (XJ Technologies).

Preliminary Results

Our preliminary simulation results indicate that transitioning from a sun-grown system to a shade-grown system as a climate adaptation strategy to increased CBB infestations is not ENPV-improving at the 5-6% recommended shading levels. That is, the baseline scenario of no shade trees yields a higher ENPV than any of the scenarios that include shade trees at any of the shading levels ranging between 2 and 10% (table 4). Under the baseline scenario of no shade, the average prevalence of highly infested coffee trees is equal to 13.8% and the ENPV over 2 years is $17.028 thousand per hectare. Intercropping coffee plants with shade trees reduces CBB prevalence by 2-8% but it also reduces the ENPV by 12-33% for the shading levels between 2 and 10%, respectively (table 4). In the shading interval considered, the benefits of reduced CBB incidence accruing to shade trees appear to be offset by the lower farm yields resulting from having smaller per-tree yields and fewer coffee trees per hectare.

[Insert table 4 here]

We conduct additional simulations to (1) examine the relationship between increased shading and CBB control; and (2) find the threshold shading level beyond which switching from a sun-grown to a shade-grown system is ENPV-improving. We find that the pest control services provided by shade trees increase at decreasing rates with the shading level (figure 2). Our results indicate that, under baseline model parameters, a farmer would need to achieve a shading level of 16% for the shade pest control benefits to justify the opportunity costs and direct costs of transitioning from a high-yield sun-grown system to a lower-yield shade-grown system (figure 3).

[Insert figure 2 here]

[Insert figure 3 here]

The baseline model does not account for the price premium or transfer shade coffee farmers may receive as a payment for ecosystem protection (Ferraro et al. 2005). We investigate how the optimal shading level changes if there is a price premium paid to shade-grown coffee farmers. We consider a price premium of $0.44/Kg, the half of which covers the costs of certification. We find that the ENPVs for the 10, 12, and 15% shading levels are $16.613, $17.366, and $18.487 per hectare, respectively. That is, the threshold shading level decreases from 16% (no price premium) to 12% under a net price premium of $0.22/Kg.

Whether higher shading levels are feasible from an agronomic standpoint depends on the particular shade tree species. For instance, in Colombia, shading levels are between 6 and 12% (100-200 trees per hectare) (Liegel and Stead 1990). If the threshold shading level is not feasible due to tree species-specific agronomic constraints (e.g., size of tree canopy), then it might be that the economically optimal shading strategies cannot be achieved. Alternatively, higher net price premiums might be needed to make the transition economically justified for recommended shade levels of 6%. For instance, we find that the net price premium would need to be more than twice as large for the 6% shading level ($0.44/Kg) to yield ENPVs higher than those of a sun-grown strategy (the ENPV of a 6% shading strategy is equal to $16.784 per hectare for a net price premium of $0.44/Kg).

Concluding Remarks and Next Steps

This paper offers a bioeconomic framework to analyze the biological and economic sustainability of planting shade trees as a climate change adaptation strategy in coffee farms. We apply the model to the coffee berry borer (CBB) diffusion under alternative shading strategies and find that shading would need to be higher than currently recommended for the pest control

benefits of shade to justify the costs of switching from a sun-grown to a shade system. Alternatively, coffee certification costs would need to be almost inexistent for shade-grown coffee price premiums to offset the direct and opportunity costs of transitioning from sun-grown to shade-grown systems as an adaptation to climate change. In reality, certification can be prohibitively expensive for developing country growers especially for groups of less than 10,000 coffee farmers (Gómez et al. 2011).

Future research should model the infestation probabilities explicitly as a function of temperature. Such exercise is particularly important to identify the IPCC climate change scenarios for which shading strategies are economically justified. The model can also be extended to incorporate spatial-dynamic pest externalities caused by the flow of CBB from neighboring coffee farms with higher CBB prevalence and lower shading levels. In such situations, shading strategies might need to allow shade tree intercropping to be spatially nonrandom. For example, alternative strategies can allow the density of shade trees to be higher at the border of coffee farms serving as the initial point of entry of CBB.

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Table 1. Overview of the modeling process

	Modeling Step	Tool
1.	*Formal model.*	
	Define bioeconomic model.	None.
2.	*Computational model.*	
2a.	*Model specification.*	Java,
	- Specify cellular automata model by defining:	AnyLogic.
	o Space and time	
	o States and state transitions	
	- Define model parameters and variables.	
2b.	*Model verification.*	
	- Conduct simulation and collect simulated data.	Java,
	- Debug to ensure consistency in model behavior between computational model and formal model.	AnyLogic.
2c.	*Model calibration*	
	Define optimization experiment that aims to find the 'optimal' CBB diffusion values using field data from the literature.	OptQuest, AnyLogic.
2d.	*Model validation*	
	Validate calibrated model by testing that the average CBB prevalence levels under sun vs. under shade fall within intervals reported in the literature.	Java, AnyLogic.
3.	*Simulation experiments*	
	Define and conduct Monte Carlo experiments: scenarios of 'no shade', and multiple shading strategies.	Java, AnyLogic.
4.	*Statistical analyses*	
	Conduct statistical tests on the differences between expected net present values.	Stata.
5.	*Sensitivity analyses*	
	Repeat steps 3 and 4 for each parameter considered in the sensitivity analysis.	

Table 2. Coffee tree yield and quality reduction parameters

Infestation state ($s_{i,j,t}$)	Berry infestation level (%)	Yield reduction (%)[a]	Quality penalty (%) [b]
$s_{i,j,t} = H$	<1	0	0
$s_{i,j,t} = I_L$	1-10	2	3
$s_{i,j,t} = I_M$	10-25	6	23
$s_{i,j,t} = I_H$	>25	20	43

[a] Duque and Baker (2003

[b] National Coffee Federation in Colombia, Price list, May 13 2013.

Table 3. CBB diffusion parameters

Parameter	Description	Value	Unit	Sources
α	Exponential probability rate parameter, no shade.	0.0100	day $^{-1}$	Preliminary model calibration.
β	Exponential probability rate parameter, shade.	0.0005	day $^{-1}$	Assumed.
L_1	Average waiting time between I_L and I_M state, no shade.	15	days	Johnson et al. (2009).
L_2	Average waiting time between I_M and I_L state, no shade.	120	days	Johnson et al. (2009) and Ruiz-Cardenas et al. (2009).

Table 3.2 Sun-grown and shade-grown coffee production parameters

			Coffee production system	
			Sun	Shade
Parameter	Description	Unit	Value[a]	Value[a]
Coffee				
$y_{(s_{i,j,t}=Healthy)}$	Yield	Kg/tree/year[b]	0.82	0.61
$p_{(s_{i,j,t}=Healthy)}$	Price[c]	USD/kg	3.16	3.16
$c_{i,j,t}$	Production cost[d]	USD/tree/year[b]	1.28	1.12
$c_{u_{i,j,0}}$	Coffee removal cost[d,e]	USD/tree	n/a	0.12
Timber				
y_{shade}	Yield	inches/tree/year[b]	n/a	0.0099295
p_{shade}	Price[d]	USD/inch	n/a	537
$c_{u_{i,j,t}}$	Production cost[d]	USD/ tree	n/a	0
ρ	Discount factor	day $^{-1}$	0.9997[f]	0.9997[f]

n/a is not applicable

[a] Parameter values are from Chamorro, Gallo and López (1994), unless otherwise noted.

[b] Note that these values are expressed in per-day terms in the model.

[c] National Coffee Federation in Colombia, Price list, May 13 2013

[d] Values are expressed in real terms.

[e] Duque and Baker (2003).

[f] Equivalent to an annual discount rate of 10%.

Table 4. Coffee shading strategies: effect on coffee berry borer (CBB) control and expected net present values (ENPV)

Shading strategy (% shade plants)	CBB prevalence (%)[a]	Change in CBB prevalence [b]	ENPV [c] (1,000$/ha)	Percent change in ENPV [d]
0 (sun-grown)	13.8 (10)	n/a	17.028 (0.05)	n/a
2	11.4 (8)	-2.4	11.455 (0.04)	-33
4	9.4 (6)	-4.5	12.375 (0.03)	-27
6	6.5 (5)	-6.0	13.236 (0.03)	-22
8	7.4 (4)	-7.4	14.084 (0.03)	-17
10	5.4 (3)	-8.4	14.904 (0.03)	-12

n/a is not applicable

[a] Average CBB prevalence over growing seasons= number of highly infested coffee plants divided by the total number of coffee plants

[b] Change in CBB prevalence=prevalence (Strategy)-prevalence (0% shading)

[c] Expectations are obtained from 300 simulations

[d] Percent change in ENPV=[ENPV (Strategy)-ENPV (0% shading)]/ ENPV (0% shading)

[e] Standard deviations in parentheses

Figure 1. Neighborhood of a coffee plant (*i, j*)

i-1, j-1	*i-1,j*	*i+1,j +1*
i,j-1	*i, j*	*i, j+1*
i+1, j-1	*i+1, j*	*i+1, j+1*

Figure 2. Production of pest control at increasing shading levels

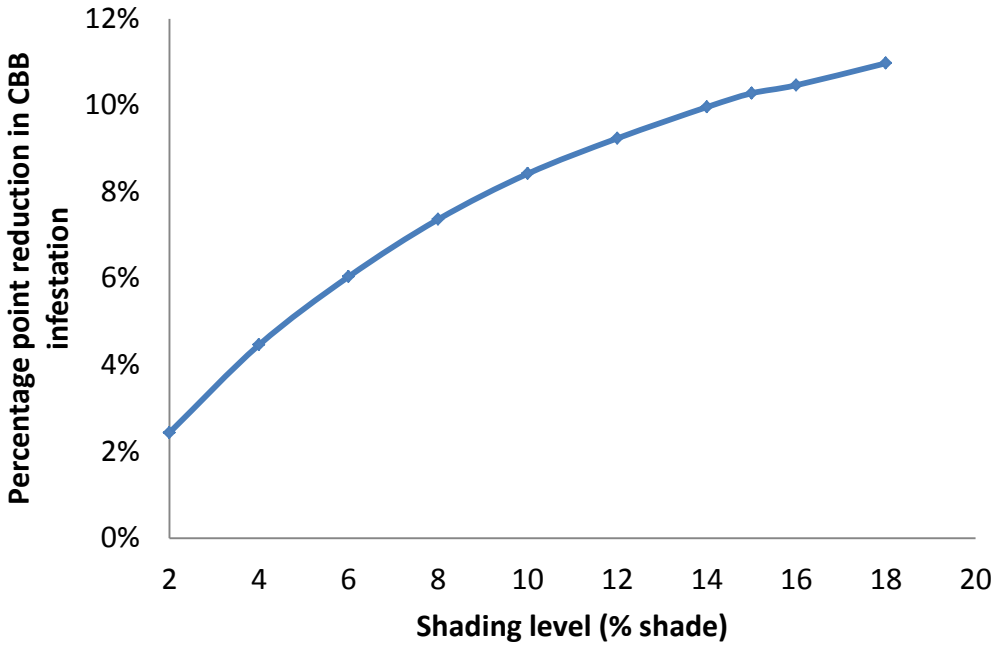
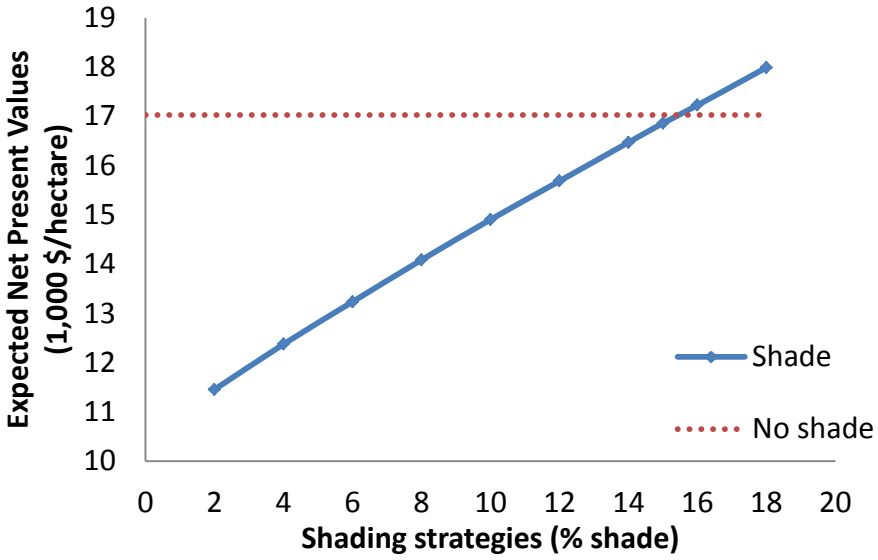


Figure 3. Effect of shading on expected net present values



Endnotes

[1] Approximately 95 percent of Colombia's coffee smallholders farm on less than 5 hectares of land (USDA FAS 2014).

[2] Note that, among the many outputs and uses of laurel, we only consider timber in this article. The tree is also grown for fruits, honey production, and ethanol production among other uses (Liegel and Stead 1990).

[3] $\boldsymbol{P}$ reads from row (states H, I_L, I_M, and I_H at time t) to column (states H, I_L, I_M, and I_H at time $t+1$).

[4] $\rho^t = \frac{1}{(1+r)^t}$, where r is the discount rate.

[5] Shade trees improve soil fertility by recycling nutrients which are not accessible to coffee trees and by increasing in the soil organic matter from leaf fall, among other mechanisms (Beer 1987).

[6] This number is chosen so as to reproduce the proportion of border coffee plants in the northwestern corner of the coffee farm that received the infestation from a neighboring farm in Ruiz-Cárdenas et al. (2009).